Does the Volatility of Volatility Risk Forecast Future Stock Returns?

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Abstract

This study investigates whether the forward-looking volatility of aggregate volatility (VOV) risk forecasts future stock returns in the US equity market. We find that stocks with higher sensitivities to changes in VOV constructed from VIX options have higher future returns than those with lower sensitivities. In particular, VOV constructed from deep out-of-the-money put options has the strongest predictive power, and the strongest predictability of VOV betas is found for investment horizons between 10-day to 1-month. Our findings are robust after considering estimation uncertainty of VOV betas and controlling for common pricing factors.

JEL Classification: G10, G11, G12

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1. Introduction

Volatility is defined as an indicator of dispersion of returns for a given security and it has been long considered as a risk indicator (Markowitz, 1952). The higher the volatility, the riskier the security. Consequently, volatility has been considered as a key concept in modern financial theory.

Volatility has long been considered as an important pricing factor in equity markets, and hence both researchers and practitioners in finance always pay a great deal of attention to volatility evolution (c.f. Bakshi and Kapadia, 2003; Mo and Wu, 2007; Bollerslev et al., 2009; Carr and Wu, 2009; Bollerslev et al., 2011, among others). This great interest in volatility might be justified differently. First, given the vital role of volatility, a stream of literature showed that forward-looking volatility measures extracted from options outperform other measures, such as historical volatility, ARCH volatility and GARCH volatility proposed by Engle (1982) and Bollerslev (1986), stochastic volatility in Heston (1993), and realized volatility calculated from high-frequency data proposed by Andersen and Bollerslev (1998) and Andersen et al. (2001) in forecasting future volatility (c.f. Blair et al., 2001; Poon and Granger, 2005; Taylor et al., 2010; Yu et al., 2010).[1] Second, some studies investigated the role of the covariances between individual stock returns and the market aggregate volatility in return prediction. For example, Ang et al. (2006) suggested the presence of a significant and negative relationship between stock returns and sensitivities to market volatility changes. Last but foremost, some literature documented that the stochastic and time-varying aspects of volatility yield heterogeneous effects on derivative pricing and investment decisions (Bakshi et al., 1997; Kaeck and Alexander, 2013; Liu and Pan, 2003).

In the meantime, over the last decades, volatility has experienced significant developments in measuring its dynamics, and leading stock markets in the US, Europe and Asia have shown that volatility is related to market liquidity and efficiency (Amihud and Mendelson, 1991; Brunnermeier and Pedersen, 2009; Shiller, 1981).[2] Given the crucial role of volatility in asset pricing and return prediction, and the stochastic feature of volatility, there has been a growing literature studying the effect of variation in volatility in stock return prediction.

One strand of literature investigated the influence of the uncertainty of volatility on stock returns and emphasized the importance of the volatility of aggregate volatility, which characterizes the distribution of stochastic volatility. For instance, Agarwal et al. (2017) and Kaeck (2018) provided evidence that volatility of aggregate volatility plays a vital role in asset pricing and has a significant risk premium. More relevantly, the other strand of literature (e.g., Chen et al., 2015; Hollstein and Prokopczuk, 2018) examined how stocks'

[1] Forward-looking volatility extracted from option data reflects expected level of underlying asset return variation before the option's expiration.

[2] In practice, the volatility index (VIX), which was introduced by the Chicago Board Options Exchange (CBOE) in 1993, has been widely used in academic research when investigating the role of aggregate volatility risk in explaining and predicting stock returns (e.g., Ang et al., 2006; Chang et al., 2013; Fu et al., 2016). The CBOE VIX provides a benchmark to measure the future 30-day market volatility. Then, the CBOE has further introduced a volatility index of the aggregate volatility measure, the VVIX, which is constructed from the out-of-the-money call and put options on the VIX. The CBOE VVIX represents the expected volatility of the future 30-day forward price of the VIX. Furthermore, given the crucial role of volatility, other countries also launched volatility indexes, such as the volatility index for FTSE100 (VFTSE) in the UK, the volatility index for Hang Seng Index (VSHI) in Hong Kong.

sensitivities to the volatility of aggregate volatility can explain or predict stock returns.[3]

However, previous studies failed to shed light on how forward-looking volatility of aggregate volatility, which is fully constructed from VIX option data, forecasts future stock returns. To distinguish our study from previous literature, we use forward-looking measures for volatility of aggregate volatility (VOV) extracted from VIX option data, and investigate the power of ***ex ante*** VOV measures in ***forecasting*** future stock returns through quintile portfolio analyses. Furthermore, given that VIX options with varying moneyness levels contain information conditional on different expectations for the future level of VIX, it is interesting to see whether different parts of the VIX volatility curve contain distinct information about stock return prediction.

First, following Hollstein and Prokopczuk (2018), we use the CBOE VVIX as a proxy of VOV and investigate the power of stocks' sensitivities to VOV in forecasting future stock returns through quintile portfolio level analyses. We find weak evidence that stocks whose returns are more positively related to daily changes in the CBOE VVIX marginally outperform those whose returns are more negatively related to daily changes in the CBOE VVIX.

Second, given that the CBOE VVIX is constructed from a limited number of VIX options with discrete strike prices, we construct a VOV measure with interpolation and extrapolation following Bakshi and Madan (2000) and Bondarenko (2014), and examine whether this VOV measure performs differently in stock return prediction. Empirical results confirm that the VOV measure constructed from the whole VIX volatility curve increases the magnitude and significance of the average premium from the zero-cost portfolio, which is long in stocks with higher sensitivities to VOV risk and short in stocks with lower sensitivities. That is, VOV measure constructed in our study outperforms the CBOE VVIX in return prediction.

Third, since options with different strike prices capture ex-ante information conditional on different anticipated market scenarios, following Fu et al. (2016) and Kaeck (2018), we construct corridor VOV measures using out-of-the-money call and put options with strikes in different ranges (corridors).[4] Different from the existing literature, we examine how these corridor VOV measures perform in return prediction and find that the VOV measure constructed from deep out-of-the-money put VIX options can yield a higher premium for the zero-cost portfolio.

Our findings on the predictive power of VOV risk and the importance of the VOV corridor measure constructed using deep out-of-the-money put VIX options are robust to a battery of robustness tests, such as considering statistical significance of VOV betas, controlling for other risk factors or firm fundamentals through double-sort portfolio analyses, and examining predictive power of VOV betas using alternative investment horizons. Our results for the predictive power of VOV betas over various horizons provide important indications for

[3]Chen et al. (2015) calculated the high-frequency implied variance using S&P500 options, and then computed the realized bipower variance of option-implied market variance. Such a measure constructed from high-frequency S&P500 options was used as a proxy of the volatility of volatility in their study. Hollstein and Prokopczuk (2018), using the CBOE VVIX, found a negative contemporaneous relationship between the sensitivities of stock returns to the volatility of aggregate volatility risk and stock returns.

[4]For example, corridor VOV calculated from deep out-of-the-money put VIX options captures information conditional on sharp decreases in the underlying VIX futures, whereas corridor VOV constructed from near-the-money call and put VIX options reflects information conditional on fluctuations of the underlying VIX futures within a narrow range.

investors about how they can adjust their trading strategies and investment horizons.

In summary, this study makes three important contributions to the existing literature. First and foremost, we decompose the VIX volatility curve and, to the best of our knowledge, we are the first to provide strong evidence that the effect of VOV beta on stock returns is asymmetric and stock premia are affected by their returns' exposure to the volatility regime. Specifically, deep out-of-the-money put VIX options contain more relevant information about stock return prediction. This finding is important for hedging and investment activities. Second, we use ex ante VOV measures in forecasting future stock returns. The application of ex ante measures in empirical analyses for return forecasting distinguishes our paper from previous related literature, such as Chen et al. (2015), which construct the VOV using high-frequency S&P500 options, and Hollstein and Prokopczuk (2018), which focus on explaining contemporaneous stock returns. Finally, we investigate the predictive horizons of VOV beta, and effectively provide a term structure of predictive power of VOV beta, which is more significant for short horizons than that for long horizons. Our results provide indications to investors on how they can adjust their trading strategies in terms of investment horizons.

The remainder of this paper is organised as follows: Section 2 presents the theoretical model, which shows the vital role of VOV in forecasting stock returns. Section 3 discusses the data and methodology. Section 4 discusses empirical results from quintile portfolio analyses, which provide evidence of the predictive power of VOV betas. Section 5 shows the results from our robustness tests. The last section concludes.

2. Theoretical Framework

The theoretical framework in Bollerslev et al. (2009), Bali and Zhou (2016), and Hollstein and Prokopczuk (2018) provides the motivation for incorporating the trade-off between volatility-of-volatility risk and return in asset pricing model. According to Epstein and Zin (1991), the logarithm of the stochastic discount factor (SDF) for the representative agent with Epstein and Zin (1989) preferences can be expresses as:

$$m_{t+1} = \theta \ln \delta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{t+1} \tag{1}$$

where δ is the subjective discount factor, θ is determined by the coefficient of relative risk aversion (γ) and the elasticity of intertemporal substitution, $\theta = (1-\gamma)/(1-\frac{1}{\psi})$, $r_{t+1} = \ln(W_{t+1}/(W_t - C_t))$ is the log return on wealth and $g_{t+1} = \Delta c_{t+1}$ is the log consumption growth. Following Bollerslev et al. (2009), Bali and Zhou (2016) and Hollstein and Prokopczuk (2018), we assume the following joint dynamics for consumption growth and its volatility:

$$g_{t+1} = \mu_g + \sqrt{\sigma^2_{g,t}} z_{t+1} \tag{2}$$

$$\sigma^2_{g,t+1} = a_\sigma + \rho_\sigma \sigma^2_{g,t} + \sqrt{q_t} z_{v,t+1} \tag{3}$$

$$q_{t+1} = a_q + \rho_\sigma q_t + \psi \sqrt{q_t} z_{q,t+1} \tag{4}$$

where a_σ and a_q are positive, $|\rho_\sigma|$ and $|\rho_q|$ is smaller than 1, and $\psi_q > 0$. μ_g, a_σ and a_q are constant mean for growth rate, the conditional variance of the growth rate and constant mean for the consumption growth volatility uncertainty, respectively. $\sigma^2_{g,t}$ represents the conditional variance of consumption growth, q_t denotes the volatility uncertainty process, while z_{t+1}, $z_{v,t+1}$, and $z_{q,t+1}$ follow independent i.i.d. $N(0,1)$ processes.

Letting ω denote the logarithm of the price-dividend ratio, or price consumption or wealth-consumption ratio, of the asset that pays the consumption endowment, Bollerslev et al. (2009) conjectured a solution for ω_t as an affine function of the state variables $\sigma^2_{g,t}$ and q_t:

$$\omega_t = A_0 + A_\sigma \sigma^2_{g,t} + A_q q_t \tag{5}$$

where

$$A_0 = \frac{log\delta + (1-\psi^{-1})\mu_g + \kappa_0 + \kappa_1[A_\sigma a_\sigma + A_q a_q]}{(1-\kappa_1)}$$

$$A_\sigma = \frac{(1-\gamma)^2}{2\theta(1-\kappa_1\rho_\sigma)}$$

$$A_q = \frac{1-\kappa_1\rho_q - \sqrt{(1-\kappa_1\rho_q)^2 - \theta^2\kappa_1^4\psi_q^2 A_\sigma^2}}{\theta\kappa_1^2\psi_q^2}$$

Under the assumption that $\gamma > 1$ and $\psi > 1$, hence $\theta < 0$, $A_\sigma < 0$, and $A_q < 0$. According to Campbell and Shiller (1988), the approximation of the return on wealth can be expressed as:

$$r_{t+1} = \kappa_0 + \kappa_1\omega_{t+1} - \omega_t + g_{t+1} \tag{6}$$

Combining equations (1), (5), and (6), we obtain a pricing kernel without reference to consumption growth (Bali and Zhou, 2016):

$$m_{t+1} = \theta \ln\delta - \frac{\theta}{\psi}\kappa_0 - \frac{\theta}{\psi}\omega_t + \frac{\theta}{\psi}\kappa_1\omega_{t+1} - \gamma r_{t+1} \tag{7}$$

Under the assumption of a conditional joint log-normal distribution with time-varying volatility for asset returns, the risk premium on an asset i is

$$E_t(r_{i,t+1}) - r_{f,t} + \frac{1}{2}Var_t(r_{i,t+1}) = -Cov(m_{t+1}, r_{i,t+1}) \tag{8}$$

Based on equations (5), (7), and (8), we can derive:

$$\begin{aligned}
&E_t(r_{i,t+1}) - r_{f,t} + \frac{1}{2}Var_t(r_{i,t+1}) \\
&= \gamma Cov_t(r_{t+1}, r_{i,t+1}) - \frac{\theta}{\psi}\kappa_1 A_\sigma Cov_t(\sigma^2_{r,t+1}, r_{i,t+1}) \\
&+ \frac{\theta}{\psi}\frac{A_\sigma\kappa_1^2(A_\sigma^2 + A_q^2\varphi_q^2) - A_q}{1+\varphi_q^2\kappa_1^4(A_\sigma^2 + A_q^2\varphi_q^2)} Cov_t(Var_{t+1}(\sigma^2_{r,t+2}), r_{i,t+1})
\end{aligned} \tag{9}$$

where $Cov_t(r_{t+1}, r_{i,t+1})$ is the time-t covariance of asset returns with aggregate returns, $Cov_t(\sigma^2_{r,t+1}, r_{i,t+1})$ denotes the time-t covariance of asset returns with $t+1$ expectations of variance, and $Cov(Q_{t+1}, r_{i,t+1})$ is the time-t covariance of asset returns with $t+1$ expectations of volatility-of-volatility over time $t+2$. Equation (9) presents a relation of current excess returns with variance and volatility-of-volatility of aggregate wealth. Based on the assumption that the current expectation of aggregate variance and aggregate volatility-of-volatility provide good proxies for next-period expectations, Hollstein and Prokopczuk (2018) further transformed Equation (9) with conditional covariances to a conditional beta representation as below:

$$E_t(r_{i,t+1}) - r_{f,t} + \frac{1}{2}Var_t(r_{i,t+1}) = \tilde{Y}\beta^M_{i,t} + \tilde{V}\beta^V_{i,t} + \tilde{Z}\beta^{VV}_{i,t} \tag{10}$$

where $\tilde{Y}$, $\tilde{V}$, and $\tilde{Z}$ are risk premia on market beta, variance beta (i.e., an asset's sensitivity to aggregate variance) and volatility-of-volatility beta (i.e., an asset's sensitivity to volatility of aggregate volatility), respectively. The market beta, $\beta^M_{i,t}$, captures the time-t comovement between return on an asset i and the market return. The variance beta, $\beta^V_{i,t}$, reflects the time-t comovement between return on an asset i and the market variance. The volatility-of-volatility beta, $\beta^{VV}_{i,t}$, indicates the time-t comovement between return on an asset i and the volatility of market volatility.

Under the framework discussed above, since $\gamma > 1$, the expected relation between market beta and stock return is positive. This is consistent with the notion that investors require higher returns when bearing higher levels of systematic market risk (i.e., positive market equity premium). Given that $\psi > 1$, $\theta < 0$, $A_\sigma < 0$, and $A_q < 0$, variance beta is expected to be negatively correlated with stock return. Previous studies (e.g., Ang et al., 2006) confirm that aggregate volatility carry a statistically significant negative price of risk (i.e., negative market volatility premium). However, there is no clear sign for how volatility-of-volatility beta predicts stock return, and the sign depends on the strength of A_σ versus A_q. Such an unclear relationship between $\beta^{VV}_{i,t}$ in Equation (10) and future stock return is of our interest.

3. Data and Methodology

3.1. Data

Data used in this study are obtained from different resources: Compustat, CRSP, OptionMetrics, the CBOE official website, and French's data library.[5] Following previous literature (e.g., Baltussen et al., 2014; Hollstein and Prokopczuk, 2018), we use all ordinary common stocks (CRSP share code of 10 and 11) traded on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) (CRSP exchange code of 1, 2 and 3) in the US market. Closed-end funds and REITs (SIC codes 6720-6730 and 6798) are excluded from our sample.

Some standard filters are applied to the stock data. First, following Amihud (2002), we exclude "penny stocks" with prices below \$1. Second, stocks with market capitalization less than \$225 million are also excluded (c.f. Baltussen et al., 2014; Hollstein and Prokopczuk, 2018). These two filters eliminate the most illiquid stocks which may lead to biased results. With respect to option data, we eliminate options with bid or ask prices smaller than \$0.025 to mitigate the effect of decimalization, and options with days to maturity shorter than 7

[5] Data for Fama-French factors are available at: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

or longer than 126 days. Also, we exclude options without available implied volatilities or violating non-arbitrage conditions. Finally, we only keep options expiring at monthly cycles.[6]

Given the evidence for the outperformance of option-implied measures compared to those calculated from historical data in forecasting future volatility and volatility of aggregate volatility (Blair et al., 2001; Hollstein and Prokopczuk, 2018; Poon and Granger, 2005; Taylor et al., 2010; Yu et al., 2010), we use forward-looking indexes quoted by the CBOE to measure the risk-neutral market volatility and volatility of aggregate volatility. More specifically, the CBOE VIX is a measure of the implied volatility of the S&P500 index in future 30 days. The CBOE VVIX measures the volatility of the aggregate volatility in future 30 days, and it is the option-implied volatility of VIX futures. We plot time series data of both the VIX and the VVIX during our sample period from January 2007 to April 2016 in Figure 1.[7] We find that, when the VIX is more volatile, we observe higher values for the VVIX, yielding a positive correlation of 35.50% between the VIX and the VVIX. Also, as for the VIX, the VVIX always exhibits a mean-reversion toward its mean. Additionally, it is obvious that dynamics of the VIX and VVIX are distinct, and we fail to find higher VVIX during turbulent period (e.g. the 2007-2008 US subprime mortgage crisis and the 2009-2012 European sovereign debt crisis).

[Figure 1]

3.2. Methodology

3.2.1. Quintile Portfolio Level Analysis

Following the theoretical framework discussed in Section 2, to examine the incremental predictive power of VOV beta in the presence of market beta and volatility beta, we first estimate VOV beta for each individual stock. Specifically, at the end of each calendar month, we estimate the following model using daily data in the previous one-month period at a rolling basis:[8]

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{M,t} - r_{f,t}) + \beta_i^{VIX}\Delta VIX_{i,t} + \beta_i^{VOV}\Delta VOV_{i,t} + \varepsilon_{i,t} \qquad (11)$$

[6] From October 2015, the CBOE has introduced weekly options. In order to be consistent in our calculation for corridor VOV measures during the whole sample period, we stick to options expiring at monthly cycles.

[7] When options on the VIX were first introduced into markets, these options were not actively traded, and the option liquidity was an important issue (Hollstein and Prokopczuk, 2018). After applying standard filters, we may not have enough number of options for our corridor VOV measures construction. So our study only uses VIX option data from January, 2007, and our measures constructed using VIX options are available from January, 2007. The availability of our corridor VOV measures matches the availability of the CBOE VVIX, which was introduced by the CBOE in January 2007.

[8] Following related previous literature (e.g., Ang et al., 2006; Chang et al., 2013; Fu et al., 2016; Hollstein and Prokopczuk, 2018), we estimate coefficients in Equation (11) using the OLS regression. Scholes and Williams (1977) and Dimson (1979) document that, for illiquid stocks, beta estimates might be biased due to the infrequent trading and nonsynchronization of returns. In order to mitigate the effect of the most illiquid stocks, we exclude stocks with prices lower than $1 and those with market capitalization below $225 million. In addition, we also follow Dimson (1979) and include lagged market returns in previous two days in the regression model for VOV beta estimation. Results are available upon request, and empirical findings are consistent with the results presented below.

where $r_{i,t}$ is the daily return of stock i on day t, $r_{M,t}$ is the market return on day t, and $r_{f,t}$ is the risk-free rate on day t. Following Chang et al. (2013), Fu et al. (2016), and Hollstein and Prokopczuk (2018), we use daily changes (i.e., the first difference) of the CBOE VIX and the CBOE VVIX to measure the aggregate volatility risk (ΔVIX in Equation (11)) and the volatility of aggregate volatility risk ($\Delta VVIX$ in Equation (11)), respectively. β_i^{MKT}, β_i^{VIX}, and β_i^{VOV} in Equation (11) correspond to $\beta_{i,t}^{M}$, $\beta_{i,t}^{V}$, and $\beta_{i,t}^{VV}$ in Equation (10).

After getting factor loadings from Equation (11) at the end of each calendar month, we use portfolio level analyses to test whether VOV betas predict future stock returns. We sort stocks in an ascending order with respect to β_i^{MKT}, β_i^{VIX}, and β_i^{VOV}, and then construct five quintile portfolios.[9] Quintile portfolio 1 consists of stocks with the lowest factor loadings and quintile portfolio 5 contains stocks with the highest factor loadings. The so-called "5-1" zero-cost portfolio is constructed by taking a long position in portfolio 5 and a short position in portfolio 1 simultaneously.[10] Through portfolio level analyses, the average return on the "5-1" portfolio (i.e., differences between average returns on portfolios 5 and those on portfolio 1) can be attributed to differences in the sorting stock characteristic (Hollstein and Prokopczuk, 2018). Thus, we examine the predictive power of β_i^{MKT}, β_i^{VIX} or β_i^{VOV} by testing whether or not the average return on the "5-1" zero-cost portfolio constructed on this stock characteristic is significantly non-zero. Especially, the relationship between β_i^{VOV} and future stock returns is of our particular interest. Also, in the test for "5-1" portfolio returns, we examine the significance of the risk-adjusted return (i.e., alpha) from the Fama-French three-factor (FF3F) model and Carhart four-factor (CH4F) model.[11]

Furthermore, in addition to the CBOE VVIX, we consider several measures to capture the VOV risk. We construct other VOV measures using VIX options as discussed in the Subsection 3.2.2, and use daily changes in these measures for ΔVOV in Equation (11).

3.2.2. VOV Measures

According to the CBOE VVIX's whitepaper, in order to construct the VVIX, the variance of the VIX is constructed using VIX options based on the following equation:

$$\sigma_T^2 = \frac{2}{T} \sum_i \frac{\Delta K_i}{K_i^2} e^{r_f T} Q(K_i) - \frac{1}{T} \left[\frac{F}{K_0} - 1 \right]^2 \tag{12}$$

where T is time to expiration, F is the forward index level desired from index option prices, K_0 is the first strike below the forward index level, K_i is the strike price of ith out-of-the-money option, ΔK_i is the interval between strike prices, r_f is the risk-free interest rate to expiration, and $Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike

[9] We also construct three tercile portfolios and ten decile portfolios for the portfolio level analyses. Findings from tercile/decile portfolio level analyses are consistent with results for quintile portfolios. Corresponding results are available upon request.

[10] Quintile portfolio analyses have been widely used in previous literature, for example, Ang et al. (2006), Chang et al. (2013), Chen et al. (2015), Fu et al. (2016), Hollstein and Prokopczuk (2018).

[11] Fama-French three-factor (FF3F) model includes market risk, a size factor, and a book-to-market factor: $r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{M,t} - r_{f,t}) + \beta_i^{SMB} SMB_{i,t} + \beta_i^{HML} HML_{i,t} + \varepsilon_{i,t}$. Based on the Fama-French three-factor model, Carhart four-factor (CH4F) model further includes an additional momentum factor: $r_{i,t} - r_{f,t} = \alpha_i + \beta_i^{MKT}(r_{M,t} - r_{f,t}) + \beta_i^{SMB} SMB_{i,t} + \beta_i^{HML} HML_{i,t} + \beta_i^{UMD} UMD_{i,t} + \varepsilon_{i,t}$.

K_i.[12] After calculating σ_T^2 shown in Equation (12) using near-term (with expiration at T_1) and next-term (with expiration at T_2) out-of-the-money call and put options, the following equation is used to compute the CBOE VVIX:

$$VVIX = 100 \times \sqrt{\left\{T_1\sigma_{T_1}^2\left[\frac{N_{T_2}-N_{30}}{N_{T_2}-N_{T_1}}\right]+T_2\sigma_{T_2}^2\left[\frac{N_{30}-N_{T_1}}{N_{T_2}-N_{T_1}}\right]\right\}\times\frac{N_{365}}{N_{30}}} \tag{13}$$

where T_1 and T_2 are two nearby maturities. Thus, $VVIX$, as the square root of weighted average of near-term variance and next-term variance using linear interpolation, is the annualized future 30-day volatility of VIX futures in percentage number.

From Equation (12), we can find that the CBOE VVIX is constructed using option prices with observable discrete strike prices across different moneyness levels. To estimate VOV accurately using the VIX volatility curve, we therefore calculate risk-neutral expectation of variance of VIX following Bakshi and Madan (2000) and Bondarenko (2014) using the equation below:

$$\sigma_{T,min,max}^2 = \frac{2e^{r_f T}}{T}\int_0^\infty \frac{Q(K,T)}{K^2}dK \tag{14}$$

Following previous literature (e.g., Stilger et al., 2017), we interpolate between observed strikes and extrapolate beyond observed strike range.[13] Based on $\sigma_{T,min,max}^2$ from Equation (14) calculated using near-term and next-term options, we construct the volatility of aggregate volatility, $VVIX_{min,max}$, and investigate how $VVIX_{min,max}$ performs in our empirical analyses.

$$VVIX_{min,max} = 100 \times \sqrt{\left\{T_1\sigma_{T_1,min,max}^2\left[\frac{N_{T_2}-N_{30}}{N_{T_2}-N_{T_1}}\right]+T_2\sigma_{T_2,min,max}^2\left[\frac{N_{30}-N_{T_1}}{N_{T_2}-N_{T_1}}\right]\right\}\times\frac{N_{365}}{N_{30}}} \tag{15}$$

Additionally, as documented in previous literature (Andersen and Bondarenko, 2007; Fu et al., 2016), different parts of the volatility curve capture distinct information. Thus, it is worthwhile to examine whether different VIX regimes perform differently in return prediction. To this end, we construct corridor VOV measures and examine the performance of each corridor VOV measure in return prediction. Following the method for computing synthetic corridor variance swaps in Carr and Madan (1998) and the method for defining the strike range, over which the implied corridor variance is calculated, in Andersen and Bondarenko (2010), we define the implied corridor variance with up and down barriers,

[12] The forward VIX level, F, in Equation (12) is the strike price at which the absolute difference between the call and put prices is the smallest.

[13] Specifically, for interpolation, we utilize implied volatilities of the available options between the lowest and the highest available moneyness for put and call options using a curve fitting method. Previous literature documents the importance of extrapolation. For example, Cassella and Gulen (2015) concentrate on the extrapolation for time-series data. For extrapolation used in model-free volatility calculation in our study, following Stilger et al. (2017), we set values beyond the quoted strike range equal to the last observed implied volatility over the moneyness range from 1/3 to 3. Such a range is enough to mitigate truncation errors as claimed by Jiang and Tian (2005). More importantly, calculating the model-free implied volatility from observed option prices using a curve-fitting method and extrapolation from endpoint implied volatility can give us an accurate estimation (Jiang and Tian, 2005).

denoted B_u and B_d, as:

$$\sigma^2_{T,B_d,B_u} = \frac{2e^{r_f T}}{T} \int_{B_d}^{B_u} \frac{Q(K,T)}{K^2} dK \tag{16}$$

The corridor VOV measure is then constructed using σ^2_{T,B_d,B_u} for near-term and next term based on the following equation:

$$VVIX_{d,u} = 100 \times \sqrt{\left\{ T_1 \sigma^2_{T_1,B_d,B_u} \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}} \right] + T_2 \sigma^2_{T_2,B_d,B_u} \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}} \right] \right\} \times \frac{N_{365}}{N_{30}}} \tag{17}$$

To get the up and down barriers for each corridor, we construct the following ratio, $R(K,T)$, using market prices of VIX call and put options (i.e., $C(K,T)$ and $P(K,T)$, respectively):

$$R(K,T) = \frac{P(K,T)}{P(K,T) + C(K,T)} \tag{18}$$

This ratio is monotonically increasing in strike price. The inverse of the ratio, $K_q = R^{-1}(q,T)$, is used to determine barriers of corridor variance swaps in a time-consistent way. In corridor VOV construction, we interpolate between observed strikes and extrapolate beyond observed strike range following previous literature (e.g., Stilger et al., 2017). Given that different parts of the VIX volatility curve capture information conditional on distinct future market conditions, we construct five corridors across moneyness levels, which are labelled $VVIX_{min,20}$ (with $B_u = K_{0.20}$ and $B_d = 1/3 \times VIX$), $VVIX_{20,40}$ (with $B_u = K_{0.40}$ and $B_d = K_{0.20}$), $VVIX_{40,60}$ (with $B_u = K_{0.60}$ and $B_d = K_{0.40}$), $VVIX_{60,80}$ (with $B_u = K_{0.80}$ and $B_d = K_{0.60}$), and $VVIX_{80,max}$ (with $B_u = 3 \times VIX$ and $B_d = K_{0.80}$).[14] Each of these five corridor VOV measures are used in the model shown in Equation (11), and factor loadings, β_i^{VOV}, are used to sort quintile portfolios, so that we examine whether different corridors of the VIX volatility curve capture distinct information about stock return prediction.

Figure 2 plots VIX option prices and implied volatilities on two specific trading days, November 20$^{\text{th}}$, 2008 (when the CBOE VIX reaches its maximum value during the sample period from January 2007 to April 2016) and August 24$^{\text{th}}$, 2015 (when the CBOE VVIX reaches its maximum value during the sample period). We also include up and down barriers for different corridors in Figure 2. It is clear that VIX options with different moneyness levels help separate different future market volatility conditions based on ex ante information. Deep out-of-the-money VIX put options, which are used to calculate $VVIX_{min,20}$, capture the information conditional on future market volatility being much lower than VIX futures (the VIX falling below $K_{0.20}$), near-the-money VIX call and put options, used for $VVIX_{40,60}$ calculation, capture the information conditional on future market volatility fluctuating around VIX futures, while deep out-of-the-money VIX call options, which are used for calculating $VVIX_{80,max}$, capture information conditional on future market volatility being much higher (the expected future VIX increasing above $K_{0.80}$). Thus, if forward looking information contained in one part of the VIX volatility curve is more relevant to return prediction, investors will be able to improve their trading strategies.

[14]We also break the VIX volatility curve into three/two parts and construct three/two corridor VOV measures following Kaeck (2018). Findings are consistent with those discussed in this paper. Empirical results are available upon requests.

[Figure 2]

After constructing five corridor VOV measures, we plot the CBOE VVIX and five corridor VOV measures (i.e., $VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$) in Figure 3. We observe that, all five corridor VOV measures are highly correlated and they are all positively correlated with the CBOE VVIX.

[Figure 3]

4. Quintile Portfolio Analyses

4.1. Descriptive Summary

From descriptive statistics shown in Panel A of Table 1, we find that, during our sample period, the range for the CBOE VIX is between 9.89 and 80.86, and the mean value of the CBOE VVIX is 87.28. For $VVIX_{min,max}$, the mean value is 85.57, which is close to the mean of the CBOE VVIX. Also, $VVIX_{min,max}$ is highly correlated with the CBOE VVIX (98.57%). With respect to five corridor VOV measures, values increase with the moneyness level. Indeed, deep out-of-the-money call corridor VOV ($VVIX_{80,max}$) has the highest mean during the sample period, whereas deep out-of-the-money put corridor VOV ($VVIX_{min,20}$) has the lowest mean. Panel B of Table 1 indicates that even though all five corridor VOV measures are highly correlated with the CBOE VVIX, these five corridor VOV measures capture distinct information.

[Table 1]

4.2. Portfolio Level Analyses Using the CBOE VVIX

Given the theoretical framework discussed in Section 2, we are particularly interested in whether sensitivities to daily changes in the CBOE VVIX predict future stock returns when market beta and volatility beta are considered. In order to obtain betas for each individual stock, we use the model as shown in Equation (11) and regress individual stock returns on the market excess returns, daily changes in the CBOE VIX, and daily changes in the CBOE VVIX at the end of each month using previous one-month daily data. Then, we investigate how market beta, volatility beta and VOV beta predict future one month stock return through quintile portfolio analyses. Corresponding results are presented in Table 2.

[Table 2]

Panel A and Panel B of Table 2 show results for portfolios constructed on β_i^{MKT} and β_i^{VIX}. These results indicate insignificant predictive power of β_i^{MKT} and β_i^{VIX} for future stock returns. The failure of the market beta in explaining or predicting stock returns has been documented in previous literature (Fama and French, 1992). With respect to the predictive power of volatility beta, Ang et al. (2006) document a significant and negative relationship between volatility beta and future stock returns during the period from 1986 to 2000. However, Chang et al. (2013) argue that the significance of the predictive power of volatility beta is time-varying and it disappears in more recent periods, especially after

2000. Thus, our findings on insignificant predictive power of volatility beta could be due to the relatively shorter and more recent sample period (i.e., January 2007 to April 2016) used in this study.

Panel C of Table 2 documents results for quintile portfolios constructed on VOV beta (β_i^{VOV}) obtained when using the CBOE VVIX. From results in Panel C, we can find that there is a marginally significant and positive relationship between sensitivities to daily innovations in the CBOE VVIX and equal-weighted quintile portfolio returns. This is inconsistent with the main finding of Hollstein and Prokopczuk (2018), who find a negative contemporaneous relationship between stock return and sensitivity to innovations in VOV. This is due to the fact that Hollstein and Prokopczuk (2018) focused on the relationship between sensitivity to innovations in VVIX and *contemporaneous* portfolio returns, whereas we focus on the *predictive* power of sensitivities to changes in the CBOE VVIX in future stock returns.

Finally, Panel D of Table 2 presents some characteristics for quintile portfolios constructed on β_i^{VOV}, i.e., factor loadings obtained from regression model as shown in Equation (11).[15] From Panel D, we find that average β^{VIX} decreases from portfolio 1 to portfolio 5 with average β^{VOV} increasing. Given the positive relation between ΔVIX and $\Delta VVIX$ (0.6700), opposite patterns in average β^{VIX} and average β^{VOV} are consistent with our expectation. However, there is no monotonic pattern in average β^{MKT} of quintile portfolios. These are consistent with patterns in factor loadings shown in Hollstein and Prokopczuk (2018).

4.3. Portfolio Level Analyses Using the Replicated VVIX

As discussed in Subsection 3.2.2, the CBOE VVIX is constructed from discrete option prices on VIX volatility curve. In this subsection, we further investigate the predictive power of a measure constructed from the whole VIX volatility curve, $VVIX_{min,max}$. Thus, instead of using the CBOE VVIX, we include the $VVIX_{min,max}$ in the regression model shown in Equation (11), and use the factor loadings on $\Delta VVIX_{min,max}$ for quintile portfolio construction. Corresponding results are shown in Table 3.

[Table 3]

From Panel A of Table 3, we find that the mean return on the equal-weighted "5-1" portfolio is significantly positive, 0.36% per month with a p-value of 0.0278. With respect to value-weighted portfolios as shown in the right panel of Table 3, we can observe a monotonic increasing pattern in portfolio returns from portfolios consisting of stocks with the lowest factor loadings to portfolios consisting of stocks with the highest factor loadings. For the value-weighted "5-1" portfolio, the average monthly return is 0.63% with a p-value of 0.0301. This positive relationship between portfolio returns and sensitivities to $\Delta VVIX_{min,max}$ is still statistically significant after controlling for factors in FF3F and CH4F models.

In addition, if we compare portfolio level analyses results in Panel A of Table 3 with those shown in Panel C of Table 2, we can easily find that the magnitude of "5-1" portfolio average returns is higher when using $VVIX_{min,max}$, no matter whether we use the equal-weighting scheme or value-weighting scheme. This indicates that the $VVIX_{min,max}$ calculated from

[15] We only report factor loadings for five quintile portfolios constructed on β_i^{VOV} since the main interest of our study is how sensitivities to the VOV risk forecast stock returns. Factor loadings for portfolios constructed on β_i^{MKT} and β_i^{VIX} are available upon request.

observed option prices using a curve-fitting method and extrapolation from endpoint implied volatility yields a more trading strategy with a higher average return.

Panel B of Table 3 documents results obtained through constructing three tercile portfolios or ten decile portfolios. These results consistently show the significant and positive predictive power of VOV beta in future one-month horizon.

4.4. Portfolio Level Analyses Using Five Corridors

Previous discussion has confirmed the importance of information captured by the VIX volatility curve in stock return prediction. Given that different parts of the VIX volatility curve capture information conditional on distinct future conditions, we examine whether different corridor VOV measures perform differently in predicting future stock returns. This helps us better understand the asymmetry of the effect of the VOV risk and stocks' sensitivities to volatility regime. We follow the method documented in Subsection 3.2.2 and construct five corridor VOV measures: $VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$ and $VVIX_{80,max}$. Each of these five corridor VOV measures is alternatively included in regression model shown in Equation (11) and factor loadings are then used in quintile portfolio construction. Corresponding results obtained using each of five corridor VOV measures are presented in Panel A to Panel E of Table 4, respectively.

[Table 4]

Panel A of Table 4 shows quintile portfolios constructed by using sensitivities to $\Delta VVIX_{min,20}$, the corridor computed using deep out-of-the-money put VIX options. In this panel, the mean monthly return on the equal-weighted "5-1" portfolio is 0.49% with a p-value of 0.0600, and the mean monthly return on the value-weighted "5-1" portfolio is 0.86% with a p-value of 0.0041. Alphas with respect to the CAPM, FF3F model and CH4F model are all significant at a 5% level. Additionally, we can easily observe a monotonically increasing pattern in returns from portfolio 1 to portfolio 5 when using either equal-weighted scheme or value-weighted scheme. Comparing with results in Panel C of Table 2 and Panel A of Table 3, if we only consider information captured by deep out-of-the-money put VIX options, we can get higher premium from the strategy of holding a long position in the portfolio consisting of stocks with the highest VOV betas and a short position in the portfolio consisting of stocks with the lowest VOV betas.

Portfolio level analyses results obtained by using $VVIX_{20,40}$ constructed from out-of-the-money put VIX options are presented in Panel B of Table 4. The average return on the equal-weighted "5-1" portfolio is positive but not statistically significant, whereas the average return on the value-weighted "5-1" portfolio is marginally significant at a 10% level (0.53% per month with a p-value of 0.0854). Such a marginally significant and positive relationship between factor loadings on $\Delta VVIX_{20,40}$ and value-weighted quintile portfolio returns is mitigated after controlling for market, size, book-to-market and momentum factors.

Panel C of Table 4 documents quintile portfolio analyses results obtained using the corridor VOV measure calculated from near-the-money call and put VIX options, $VVIX_{40,60}$. The left panel presents results for equal-weighted portfolios. The average monthly return on the equal-weighted "5-1" portfolio is marginally significant (0.34% with a p-value of 0.0894).

When it comes to value-weighted portfolios, we can observe a monotonically increasing pattern in returns from portfolio 1 to portfolio 5. The difference between monthly return on portfolio 5 and that on portfolio 1 has the time-series mean of 0.64% with a p-value of 0.0725.

Panel D of Table 4 presents portfolios constructed on factor loadings on $\Delta VVIX_{60,80}$, which is calculated using out-of-the-money call VIX options. For equal-weighted quintile portfolio returns, we find a positive relationship between portfolio returns and stocks' sensitivities to $\Delta VVIX_{60,80}$. The mean return on the equal-weighted "5-1" portfolio is 0.32% per month with a p-value of 0.0864. Such a positive relationship becomes insignificant when constructing portfolios using the value-weighted scheme.

Finally, portfolio level analyses results obtained using $VVIX_{80,max}$ in the regression model are shown in Panel E of Table 4. In this panel, we can find that equal-weighted quintile portfolio returns are significantly and positively correlated with stocks' factor loadings on daily changes in corridor VOV calculated using deep out-of-the-money call options. The average monthly return on the equal-weighted "5-1" portfolio is 0.34% with a p-value of 0.0287. Such a significant and positive relationship does not hold when portfolios are constructed using the value-weighted scheme.

From all five panels of Table 4 discussed above, we observe that the magnitude of the mean return on the "5-1" portfolios is the highest when we focus on a most left part of the VIX volatility curve captured by the deep out-of-the-money put VIX options. Comparisons among different corridor VOV measures show that the deep out-of-the-money put VIX options contain more relevant information about stock return prediction, and investors are able to boost the premium by focusing on the most left part of the VIX volatility curve.

The superior forecasting power of the deep out-of-the-money put VIX options might be due to following reasons. First, different parts of the VIX volatility curve capture ex ante information conditional on different possible market scenarios at the expiration of options in the future (as shown in Figure 2). Out-of-the-money call options capture forward looking information conditional on potential market volatility increase (i.e., market turmoil), whereas out-of-the-money put options capture forward looking information conditional on potential market volatility decrease (i.e., relatively calm periods). Different stocks' correlations with risk factors all become higher during periods of market turmoil, while stock returns' sensitivities to risk factors become more diverse during calm periods. This asymmetry indicates that stock premia are affected by their returns' exposure to volatility regime. Therefore, it is easier to identify how VOV beta forecasts future stock returns using the measure constructed on information conditional on market calmness. Second, given the crucial role of volatility risk in asset pricing, more and more investors realize the importance of hedging volatility risk. After hedging, investors can get rid of the unfavourable risk and benefit from high volatility. Then, they care more about the potential decreases in future volatility, and stock sensitivities to information conditional on decreases in volatility becomes more relevant in return forecasting.

5. Robustness Tests

5.1. Portfolio Analyses Considering Statistical Significance

In Section 4, we conducted portfolio level analyses focusing on VOV betas, which are obtained from time-series regressions as shown in Equation (11). However, focusing on the magnitude of beta coefficients may ignore the errors in beta estimation. So, we would like to investigate whether the predictive power of VOV betas in stock returns is robust after considering uncertainty in beta estimation and statistical significance of these betas. Specifically, we check whether the positive relationship between VOV beta and future stock returns remains if we only focus on stocks with statistically significant VOV betas.

Among stocks included in our sample, on average, around 15% of stocks have significant VOV beta estimated from Equation (11) at a 5% level.[16] Given the smaller number of stocks with significant VOV betas, to construct well-diversified portfolios, we form two portfolios: one portfolio consists of all stocks with significantly positive VOV betas (Portfolio P), and the other portfolio consists of all stocks with significantly negative VOV betas (Portfolio N). The zero-cost "P-N' portfolio is constructed by holding a long position in the former portfolio and a short position in the latter. The results are presented in Table 5.

[Table 5]

Results in Table 5 show that our findings in Section 4 hold for a smaller sample consisting of stocks with statistically significant VOV betas. That is, we find that VOV beta positively predicts future stock returns. Furthermore, the corridor VOV constructed using deep out-of-the-money put VIX options has the most significant predictive power, and trading strategy based on this corridor generates higher returns than those strategies based on the CBOE VVIX, the replicated $VVIX_{min,max}$, and other corridor measures do.

5.2. Portfolio Analyses during Turbulent Periods

Our sample period is from January 2007 to April 2016, which covers the US subprime mortgage crisis (2007-2008) and the European sovereign debt crisis (2009-2012). During the crisis period, the market volatility is higher (as shown in Figure 1), so we examine whether the predictive power of VOV betas persists during highly volatile period by focusing on the subsample from January 2007 to December 2012.[17] Corresponding results are presented in

[16] In order to control for the autocorrelation and heterogeneity in error terms in the time-series regressions as shown in Equation (11), we use the Newey-West standard errors and further calculate the t-statistics and p-values for coefficients. Furthermore, we aim to examine the incremental predictive power of volatility of volatility risk with the presence of market risk and volatility risk. Including market excess return, daily changes in volatility, and daily changes in volatility of volatility in the same model may cause a multicollinearity issue, which leads to an upward bias in the estimation of standard errors of coefficients and lowers t-statistics of coefficients. For statistically significant VOV betas obtained from our previous analyses, their significance remains even after controlling for multicollinearity issue. Thus, by using only the significant VOV betas, we can be reasonably confident that our results are less likely to be affected by the potential multicollinearity issue.

[17] As shown in Figure 1, even though market volatility is higher during the crisis period, we fail to observe distinct patterns of the volatility of volatility during the crisis period.

Table 6.[18]

[Table 6]

Table 6 shows results that are consistent with our findings in Section 4. Using $VVIX_{min,20}$ yields the highest and statistically significant return on the "5-1" zero-cost portfolio. Thus, our results for the turbulent subsample period still indicate that the most left part of the VIX volatility curve contains more relevant information about stock return prediction.

5.3. Double-Sort Portfolio Analyses

In Section 4, when investigating the relationship between VOV betas and future stock returns, we did not simultaneously take other potential stock characteristics into consideration. Given the importance of the market beta and sensitivities to innovations in market volatility documented in previous literature (e.g., Ang et al, 2006), it is important to check whether our previous results are robust after considering other risk factors and firm characteristics. Thus, in this section, we check the robustness of the relationship between VOV betas and future stock returns using double-sort quintile portfolio analyses.

To be more specific, we first sort all stocks into five groups based on the controlled characteristic. Then, within each group, stocks are further divided into five groups based on their factor loadings on daily changes in VOV measures (i.e., the CBOE VVIX, the replicated $VVIX_{min,max}$, or each of five corridor VOV measures). Thus, we construct 25 portfolios in total. After this, we average returns on five portfolios with similar factor loadings on daily changes in VOV measures across five controlled characteristic groups. Through this double-sort process, we are able to examine how VOV betas predict stock returns after controlling for other stock characteristics.[19]

5.3.1. Double-Sort Portfolio Analyses Controlling for Market Beta

First of all, we check whether VOV beta predicts stock returns after controlling for the effect of market beta. The results are presented in Panel A of Table 7. These results indicate that, after controlling for market beta, VOV beta still predicts stock returns in a positive way. Additionally, among all five corridors, the deep out-of-the-money put corridor captures more information about stock return prediction, and the trading strategy based on this corridor can bring higher future returns.

[Table 7]

5.3.2. Double-Sort Portfolio Analyses Controlling for Volatility Beta

Given that previous studies document the predictive power of sensitivities to aggregate volatility risk (Ang et al., 2006; Fu et al., 2016) and that aggregate volatility and volatility

[18] Table 6 only presents average returns on quintile portfolios and "5-1" portfolios. Results for CAPM α, FF3F α, and CH4F α are available upon requests.

[19] We only present results for average returns obtained by constructing 25 value-weighted portfolios in this section. Results for CAPM α, FF3F α, and CH4F α, and those results obtained by constructing 25 equal-weighted portfolios are available upon requests.

of aggregate volatility are correlated, it is essential to examine whether the predictive power of VOV beta remains significant after controlling for the effect of β_i^{VIX}. Results for double-sort portfolios on β_i^{VOV} with β_i^{VIX} controlled are shown in Panel B of Table 7. Results show that, after controlling for the effect of β_i^{VIX}, the positive relationship between VOV beta and future stock returns is mitigated. However, factor loadings on the VOV measure constructed using deep out-of-the-money put VIX options ($VVIX_{min,20}$) still significantly predict future one-month returns in a positive way (with a p-value of 0.0632). This finding highlights the importance of the most left part on the VIX volatility curve in forecasting stock returns.

5.3.3. Double-Sort Portfolio Analyses Controlling for Firm Size

In Section 4, we found that the positive relationship between value-weighted portfolio returns and VOV betas is more statistically significant when the corridor is constructed using deep out-of-the-money put VIX options, whereas the positive relationship between equal-weighted portfolio returns and VOV betas is more statistically significant when the corridor is constructed using deep out-of-the-money call VIX options. So it is interesting to examine whether the predictive power of sensitivities to VOV risk in stock returns can be affected by firm size. Corresponding results are documented in Panel C of Table 7. After controlling for firm size, there is still a significant and positive relationship between sensitivities to daily changes in volatility of aggregate volatility and stock returns. The strategy based on $VVIX_{min,20}$ still yields the highest mean return over the sample period.

5.3.4. Double-Sort Portfolio Analyses Controlling for Book-to-Market Ratio

Previous literature (Fama and French, 1993) documented the existence of the value (book-to-market) anomaly, which means that stocks with higher book-to-market ratios outperform those with lower book-to-market ratios. So we check whether the predictive power of VOV betas can be explained by the value effect. The results obtained after controlling for the book-to-market ratio are presented in Panel D of Table 7. After controlling for the value effect, we still find that higher β_i^{VOV} obtained using $\Delta VVIX_{min,20}$ predicts higher future stock returns. Among five corridor volatility of aggregate volatility measures, β_i^{VOV} obtained using $\Delta VVIX_{min,20}$ has the strongest positive predictive power.

5.3.5. Double-Sort Portfolio Analyses Controlling for Historical Return

Given the power of historical stock performance in predicting future returns, such as the momentum effect (Jagadeesh and Titman, 1993) and the contrarian effect (De Bondt and Thaler, 1985 and 1987), we also check the persistence of the predictive power of β_i^{VOV} after controlling for the effect of historical return, i.e., previous 12 to 2 months return ($r_{t-12,t-2}$) and previous 1 month return (r_{t-1}), as shown in Panel E and Panel F of Table 7, respectively. Both panels show that our previous findings about the predictive power of VOV beta and the importance of the corridor constructed using deep out-of-the-money put VIX options still hold after controlling for historical return.

5.3.6. Double-Sort Portfolio Analyses Controlling for Illiquidity

Finally, we control for the Amihud's (2002) illiquidity measure, which is demonstrated to be negatively related to stock returns. Results for controlling for illiquidity are documented in Panel G of Table 7. From Panel G, we can find that, after controlling for illiquidity, sensitivity to daily changes in volatility of aggregate volatility still marginally predicts future stock returns. In addition, compared with other parts of the VIX volatility curve, the most left part (i.e., the deep out-of-the-money put VIX options) contains more relevant information about stock return prediction.

In summary, after considering the statistical significance of VOV beta, concentrating on turbulent periods, or controlling for market beta, volatility beta, firm size, book-to-market ratio, historical stock return, or illiquidity through double-sort process, our previous findings about the predictive power of VOV betas still hold. Meanwhile, the robustness analyses further confirm that deep out-of-the-money put options capture more relevant information about stock return prediction.

5.4. Predictive Horizon of VOV Beta

In sections 4, we reported that higher VOV beta predicts higher future one-month stock return. Whether such predictive power holds over various horizons needs to be further tested. Thus, in this subsection, we assume that portfolios are held over periods from 5 trading days to 3 calendar months after the construction. Corresponding results are shown in Table 8.[20]

[Table 8]

First, we look at three horizons shorter than one month. Panel A of Table 8 documents results for value-weighted quintile portfolios constructed on different VOV measures over 5 trading days after portfolio construction. From these results, we only find limited evidence for the predictive power of VOV betas.

If we extend the test horizon to 10 trading days, from Panel B of Table 8, we find that sensitivity to daily changes in $VVIX_{min,max}$ significantly predicts future 10-day stock returns. Among five corridor VOV measures, VOV beta obtained when using $VVIX_{min,20}$ has the strongest predictive power (i.e., the corresponding value-weighted "5-1" portfolio has the average 10-day return of 0.64% with a p-value of 0.0035). Corridor VOV measures constructed using out-of-the-money put VIX options, near-the-money call and put VIX options, out-of-the-money call VIX options all significantly and positively predict future 10-day stock returns.

As documented in Panel C of Table 8, the predictive power of VOV beta still persists after extending the holding period to 15 trading days after portfolio construction. Among five corridor VOV measures, $VVIX_{min,20}$ still has the strongest predictive power (i.e., the average 15-day return on the value-weighted "5-1" portfolio is 0.71% with a p-value of 0.0076).

[20]Due to space limitation, we only present results for average returns obtained by constructing value-weighted quintile portfolios in this subsection. Results for CAPM α, FF3F α, and CH4F α, and those results obtained by constructing equal-weighted quintile portfolios are available upon requests.

Then, we investigate whether the predictability of VOV beta holds for horizons longer than one month. Panel E of Table 8 shows the quintile portfolio analyses results for two-month horizon. We do not find any supportive evidence for significant predictive power of different VOV measures. Furthermore, as shown in Panel F of Table 8, when extending the predictive horizon to three months, there is still limited evidence for the predictability of VOV beta.

Thus, from our analyses, we conclude that the predictive power of sensitivity to daily changes in VOV measures is significant for period shorter than one month, and the predictability is the most significant for 10-day horizon. However, the evidence for the predictive power of VOV beta over two months or three months is very limited.

6. Conclusion

In this study, we provide plenty of evidence that the VOV beta has a significant and positve power in forecasting future returns. First, by using the CBOE VVIX as a proxy of volatility of aggregate volatility, we find that stocks with higher sensitivities to daily changes in VOV (i.e., higher VOV betas) marginally outperform those with lower sensitivities (i.e., lower VOV betas). This finding obtained using the CBOE VVIX confirms that the VIX volatility curve captures important information about stock return prediction, and VOV beta has incremental predictive power, in particular because CBOE VVIX includes information on investor's sentiment.

Furthermore, given that the CBOE VVIX is constructed using option data with discrete strike prices, we also construct a VOV measure using the interpolation and extrapolation method documented in Bakshi and Madan (2000) and Bondarenko (2014), which yields a stronger and more significantly positive relationship between stock returns and VOV beta.

More importantly, we distinguish different parts of the VIX volatility curve and examine whether different corridor VOV measures capture significantly distinct information on stock return prediction. Our findings confirm that the most left part of the VIX volatility curve (i.e., deep out-of-the-money put VIX options) reflects more relevant forward-looking information. Focusing on this part of the VIX volatility curve can increase both the magnitude and the significance of the return on the trading strategy which holds a long position in stocks with the highest sensitivities to daily changes in deep out-of-the-money put corridor VOV and a short position in stocks with the lowest sensitivities. Our findings support that the effect of VOV risk on stock returns is asymmetric. Also, empirical results highlight that stock premia are affected by their sensitivities to volatility regime.

Our findings about the predictive power of VOV betas and the importance of the corridor VOV measure constructed from deep out-of-the-money put VIX options are robust to a set of checks: portfolio level analyses using a smaller sample of stocks with statistically significant VOV betas, portfolio level analyses during turbulent subsample periods, double-sort portfolio analyses, and analyses on predictive horizon of VOV betas.

Our findings have vital implications by confirming the importance of the volatility of aggregate volatility risk in forecasting future stock returns. Specifically, our findings on different corridor VOV measures and various investment horizons provide valuable indications for investors' trading activities in equity markets. That is, the trading strategy constructed based on deep out-of-the-money put VIX options yields the highest mean return in all controlled cases. Furthermore, the predictive power of sensitivity to daily changes in VOV is the strongest for 10-day horizon and it lasts until future one-month horizon, and investors can adjust their investment horizons if they construct trading strategies based on VOV risk.

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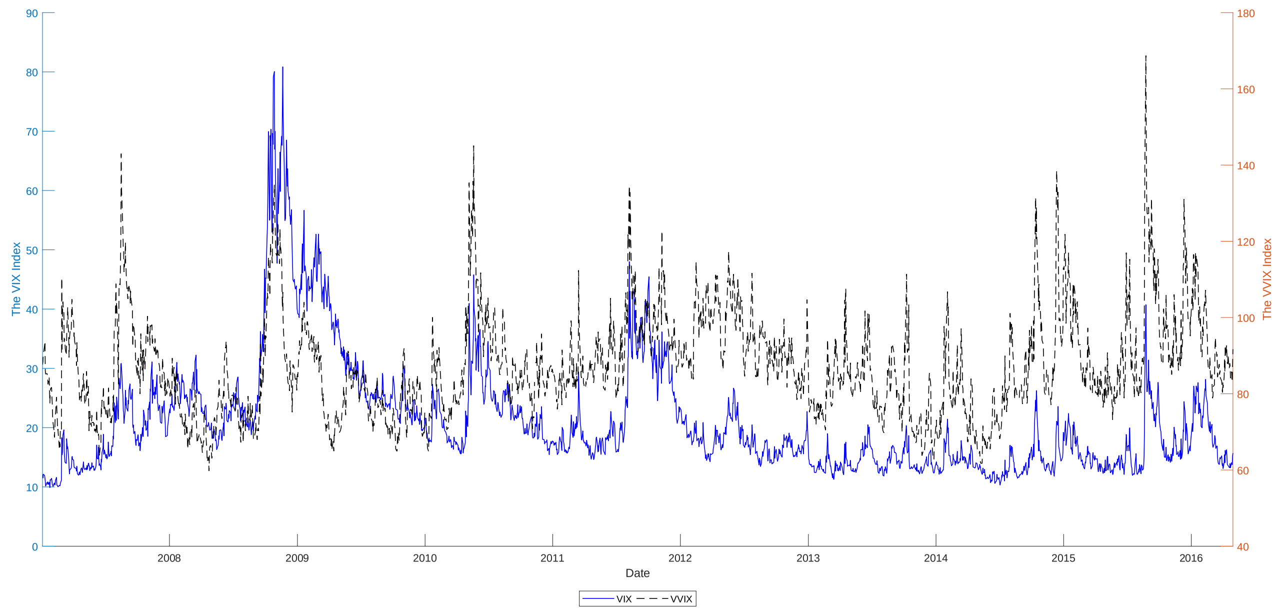
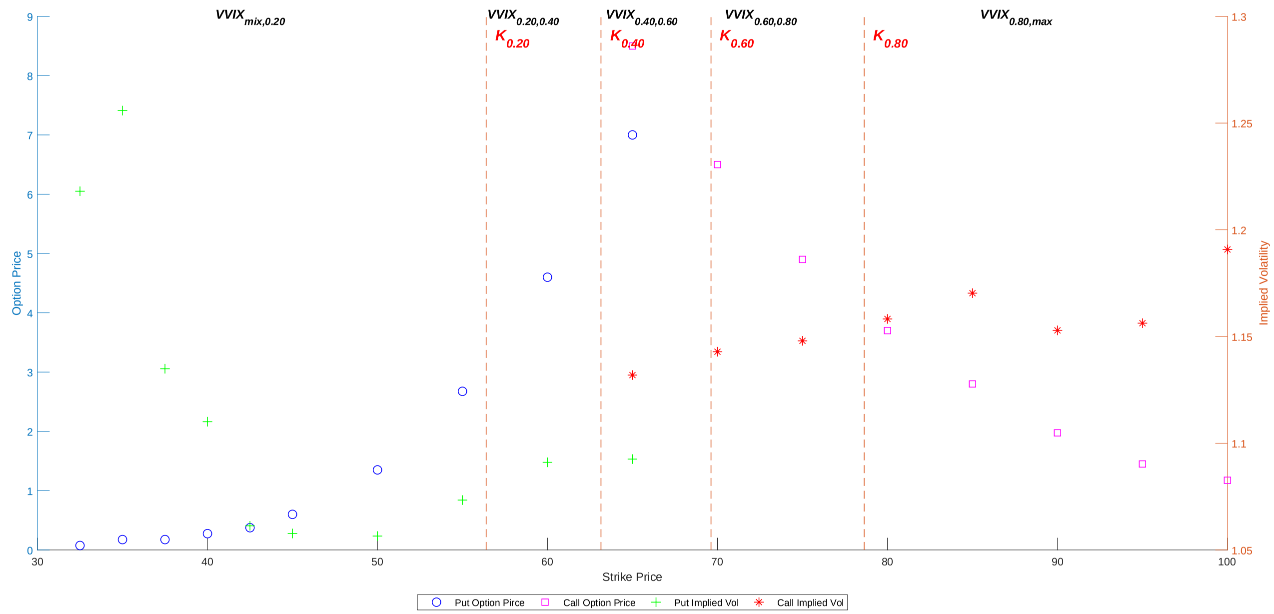
Figure 1: The CBOE VIX and The CBOE VVIX



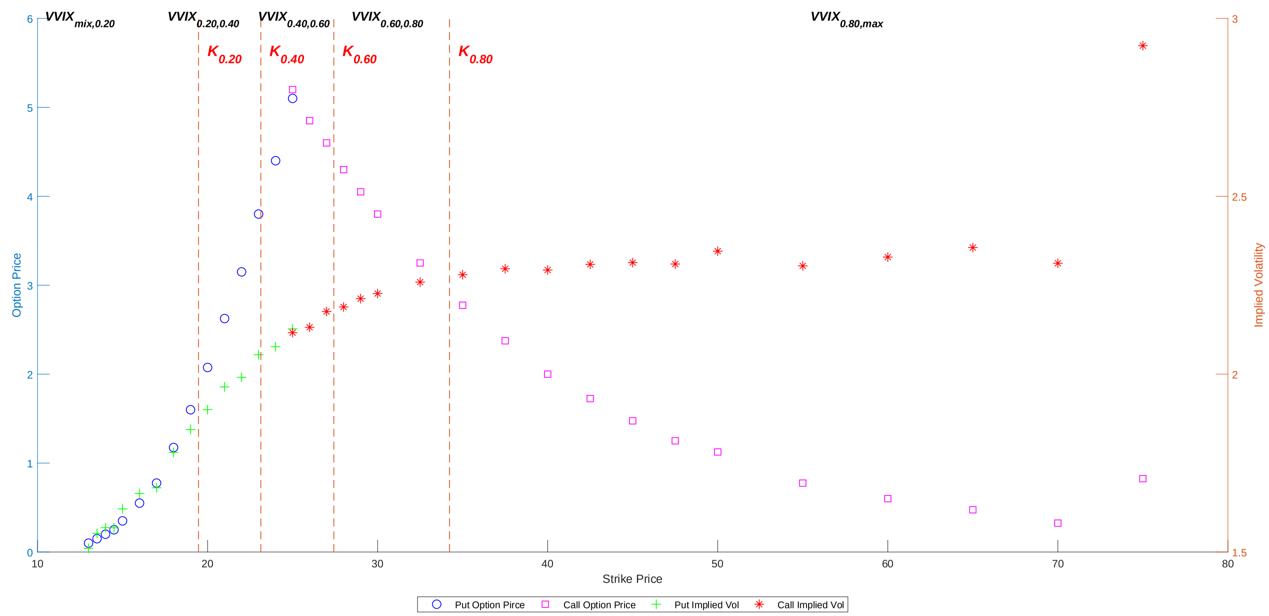
Notes: Figure 1 plots the CBOE VIX and CBOE VVIX during the period from January 2007 to April 2016.

Figure 2: VIX Option Prices and Implied Volatility

Panel A: VIX Options on Nov 20$^{\text{th}}$, 2008 (Expiration Date: Dec 17$^{\text{th}}$, 2008)

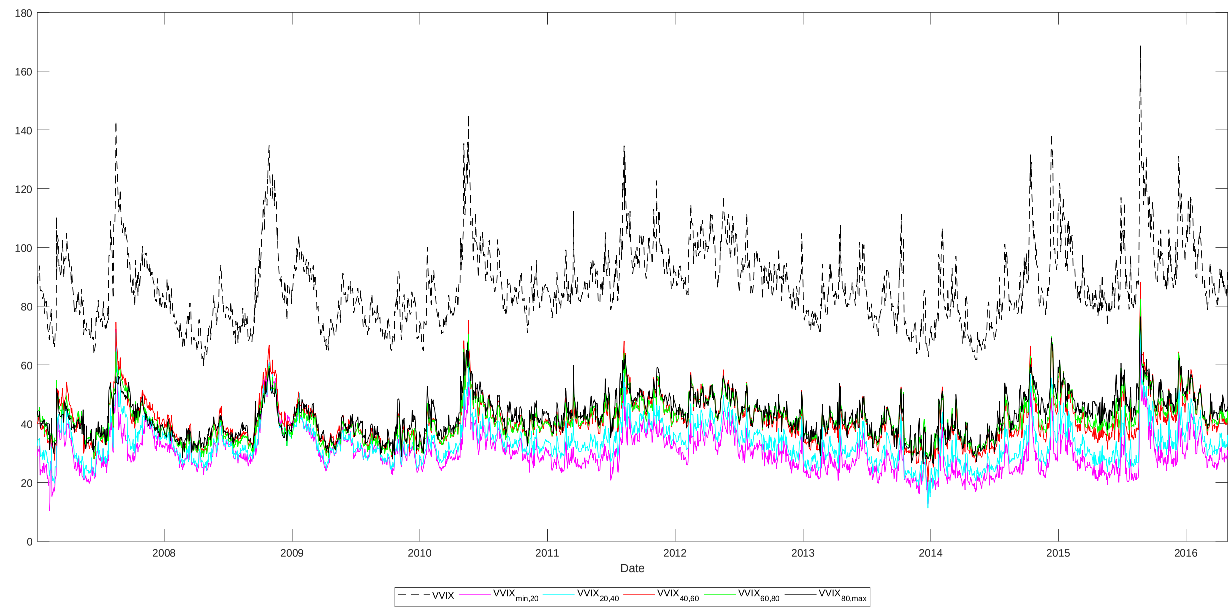


Panel B: VIX Options on Aug 24^{th}, 2015 (Expiration Date: Sep 16^{th}, 2015)



Notes: Panel A of Figure 2 plots prices and implied volatilities for VIX options on November 20^{th}, 2008, and all these VIX options have the expiration date of December 17^{th}, 2008. Panel B of Figure 2 plots prices and implied volatilities for VIX options on August 24^{th}, 2015, and all these VIX options have the expiration date of September 16^{th}, 2015. In both Panel A and Panel B of Figure 2, we also include up and down barriers for different corridors.

Figure 3: The CBOE VVIX and Replicated Corridor VOV Measures



Notes: Figure 3 plots the CBOE VVIX together with five corridor VOV measures during the period from January 2007 to April 2016.

Table 1: Summary Statistics

Notes: Following summary statistics are obtained using daily observations during the period from January 2007 to April 2016.

Panel A: Descriptive Summary

	VIX	$VVIX$	$VVIX_{min,max}$	$VVIX_{min,20}$	$VVIX_{20,40}$	$VVIX_{40,60}$	$VVIX_{60,80}$	$VVIX_{80,max}$
Mean	21.1868	87.2813	85.5656	30.2944	33.694	41.1059	41.4051	42.8521
Median	18.31	85.36	83.3733	29.3971	32.7734	39.9193	40.7153	42.5806
Std Dev	9.8757	13.4244	14.7489	6.8913	6.8474	7.46244	6.8823	6.9832
Kurtosis	6.7603	1.5395	1.4065	2.234	1.8451	1.68859	1.1247	0.2275
Skewness	2.2802	0.9313	0.8482	1.03864	0.9046	0.95394	0.7671	0.4205
Minimum	9.89	59.74	47.5829	10.2447	11.2338	20.263	27.6635	26.3231
Maximum	80.86	168.75	173.887	72.1633	74.5748	88.0746	82.2042	76.3651

Panel B: Correlation Matrix

	$VVIX$	$VVIX_{min,max}$	$VVIX_{min,20}$	$VVIX_{20,40}$	$VVIX_{40,60}$	$VVIX_{60,80}$
$VVIX_{min,max}$	0.9857					
$VVIX_{min,20}$	0.8115	0.8603				
$VVIX_{20,40}$	0.933	0.964	0.9455			
$VVIX_{40,60}$	0.9822	0.9923	0.8526	0.9642		
$VVIX_{60,80}$	0.974	0.9603	0.6979	0.8645	0.9584	
$VVIX_{80,max}$	0.9198	0.9237	0.6387	0.8037	0.8924	0.9489

Table 2: Portfolio Level Analyses Using Market Excess Return, the CBOE VIX and VVIX

Notes: At the beginning of each month, we form five quintile portfolios based on market beta, β_i^{MKT}, volatility beta, β_i^{VIX}, or volatility of volatility beta, β_i^{VOV}. Portfolio 1 consists of stocks with the lowest betas, whereas portfolio 5 consists of stocks with the highest betas. Portfolio "5-1" is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Quintile Portfolios Constructed on β_i^{MKT}												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0047	0.0068	0.0071	0.0074	0.0050	0.0002	0.0049	0.0070	0.0083	0.0061	0.0038	-0.0011
P-value						(0.9541)						(0.8433)
CAPM α	-0.0012	0.0007	0.0002	-0.0003	-0.0040	-0.0029	0.0003	0.0020	0.0021	-0.0012	-0.0051	-0.0054
P-value						(0.2958)						(0.1108)
FF3F α	-0.0017	0.0010	0.0007	0.0008	-0.0024	-0.0007	-0.0006	0.0019	0.0022	-0.0007	-0.0035	-0.0029
P-value						(0.7651)						(0.2982)
CH4F α	-0.0017	0.0010	0.0007	0.0009	-0.0023	-0.0006	-0.0007	0.0019	0.0022	-0.0006	-0.0034	-0.0027
P-value						(0.7665)						(0.2651)

Panel B: Quintile Portfolios Constructed on β_i^{VIX}												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0064	0.0058	0.0076	0.0062	0.0050	-0.0013	0.0068	0.0063	0.0048	0.0053	0.0045	-0.0023
P-value						(0.4278)						(0.4591)
CAPM α	-0.0015	-0.0009	0.0011	-0.0005	-0.0028	-0.0013	0.0001	0.0007	-0.0006	-0.0005	-0.0025	-0.0026
P-value						(0.4549)						(0.4243)
FF3F α	-0.0012	-0.0004	0.0017	0.0001	-0.0018	-0.0007	-0.0006	0.0009	-0.0006	-0.0006	-0.0020	-0.0014
P-value						(0.6800)						(0.6212)
CH4F α	-0.0011	-0.0004	0.0017	0.0001	-0.0018	-0.0007	-0.0005	0.0008	-0.0006	-0.0006	-0.0020	-0.0015
P-value						(0.6750)						(0.6102)

Panel C: Quintile Portfolios Constructed on β_i^{VOV}

	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0043	0.0056	0.0063	0.0078	0.0070	0.0027*	0.0029	0.0050	0.0058	0.0078	0.0058	0.0028
P-value						(0.0992)						(0.3078)
CAPM α	-0.0033	-0.0009	-0.0001	0.0009	-0.0012	0.0022	-0.0037	-0.0004	0.0003	0.0020	-0.0015	0.0023
P-value						(0.2053)						(0.4185)
FF3F α	-0.0023	-0.0002	0.0003	0.0013	-0.0008	0.0015	-0.0034	-0.0002	0.0004	0.0018	-0.0019	0.0015
P-value						(0.3428)						(0.5868)
CH4F α	-0.0022	-0.0002	0.0003	0.0014	-0.0007	0.0015	-0.0034	-0.0002	0.0003	0.0018	-0.0019	0.0015
P-value						(0.3399)						(0.5574)

Panel D: Factor Loadings for Quintile Portfolios Constructed on β_i^{VOV}

	1	2	3	4	5	5-1
β^{MKT}	1.0883	0.9479	0.9216	1.0243	1.3100	0.2217***
						(0.0101)
β^{VIX}	0.5432	0.1788	-0.0113	-0.1810	-0.5008	-1.0440***
						(0.0000)
β^{VOV}	-0.2636	-0.0869	0.0016	0.0894	0.2709	0.5345***
						(0.0000)

Table 3: Portfolio Level Analyses Using the Replicated VVIX Index ($VVIX_{min,max}$)

Notes: Panel A of Table 3 presents results for quintile portfolio analysis, whereas Panel B of Table 3 presents results for tercile or decile portfolio analysis. At the beginning of each month, we form portfolios based on volatility of volatility beta, β_i^{VOV}, obtained using replicated VVIX index, $VVIX_{min,max}$. The zero-cost long-short portfolio is constructed by holding a long position in portfolio consisting of stocks with the highest betas and a short position in portfolio consisting of stocks with the lowest betas. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Quintile Portfolios Constructed on β_i^{VOV}

	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0037	0.0057	0.0062	0.0082	0.0073	0.0036**	0.0022	0.0045	0.0050	0.0069	0.0085	0.0063**
P-value						(0.0278)						(0.0301)
CAPM α	-0.0041	-0.0011	-0.0003	0.0013	-0.0005	0.0036**	-0.0045	-0.0011	-0.0005	0.0013	0.0015	0.0060*
P-value						(0.0430)						(0.0567)
FF3F α	-0.0032	-0.0004	0.0002	0.0016	0.0002	0.0034*	-0.0042	-0.0010	-0.0005	0.0009	0.0014	0.0057*
P-value						(0.0599)						(0.0636)
CH4F α	-0.0032	-0.0004	0.0002	0.0017	0.0002	0.0034*	-0.0042	-0.0010	-0.0005	0.0009	0.0015	0.0058**
P-value						(0.0600)						(0.0496)

Panel B: Long-Short Portfolios Constructed on β_i^{VOV}

	Tercile Portfolios						Decile Portfolios					
	Equal-Weighted			Value-Weighted			Equal-Weighted			Value-Weighted		
	1	3	3-1	1	3	3-1	1	10	10-1	1	10	10-1
Mean	0.0043	0.0079	0.0036***	0.0028	0.0075	0.0047***	0.0029	0.0064	0.0035	0.0013	0.0078	0.0065
P-value			(0.0079)			(0.0071)			(0.1056)			(0.1126)
CAPM α	-0.0031	0.0005	0.0036**	-0.0034	0.0011	0.0045**	-0.0054	-0.0018	0.0036	-0.0064	0.0003	0.0067
P-value			(0.0145)			(0.0200)			(0.1052)			(0.1050)
FF3F α	-0.0022	0.0010	0.0033**	-0.0031	0.0010	0.0041**	-0.0045	-0.0012	0.0032	-0.0065	0.0005	0.0070*
P-value			(0.0220)			(0.0343)			(0.1549)			(0.0977)
CH4F α	-0.0022	0.0011	0.0033**	-0.0031	0.0010	0.0041**	-0.0044	-0.0012	0.0032	-0.0064	0.0006	0.0071*
P-value			(0.0218)			(0.0309)			(0.1561)			(0.0723)

Table 4: Portfolio Level Analyses Using Five Corridor VOV Measures

Notes: At the beginning of each month, we form five quintile portfolios based on volatility of volatility beta, β_i^{VOV}, obtained using each of corridor VOV measures ($VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$). Portfolio 1 consists of stocks with the lowest betas, whereas portfolio 5 consists of stocks with the highest betas. Portfolio "5-1" is constructed by holding a long position in portfolio 5 and a short position in portfolio 1. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Quintile Portfolios Constructed When Using $VVIX_{min,20}$												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0030	0.0060	0.0071	0.0071	0.0078	0.0049*	0.0004	0.0047	0.0055	0.0068	0.0090	0.0086***
P-value						(0.0600)						(0.0041)
CAPM α	-0.0051	-0.0007	0.0005	0.0004	0.0003	0.0054**	-0.0066	-0.0011	0.0004	0.0010	0.0025	0.0091***
P-value						(0.0267)						(0.0027)
FF3F α	-0.0045	-0.0002	0.0010	0.0010	0.0010	0.0055**	-0.0066	-0.0014	0.0005	0.0011	0.0026	0.0092***
P-value						(0.0241)						(0.0021)
CH4F α	-0.0044	-0.0002	0.0010	0.0010	0.0011	0.0055**	-0.0066	-0.0013	0.0004	0.0011	0.0026	0.0093***
P-value						(0.0241)						(0.0020)

Panel B: Quintile Portfolios Constructed When Using $VVIX_{20,40}$												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0044	0.0055	0.0070	0.0074	0.0069	0.0025	0.0018	0.0038	0.0051	0.0085	0.0071	0.0053*
P-value						(0.2434)						(0.0854)
CAPM α	-0.0033	-0.0013	0.0006	0.0005	-0.0012	0.0020	-0.0050	-0.0019	-0.0002	0.0026	0.0001	0.0051*
P-value						(0.3457)						(0.0882)
FF3F α	-0.0023	-0.0005	0.0010	0.0011	-0.0009	0.0015	-0.0049	-0.0013	-0.0003	0.0027	-0.0004	0.0045
P-value						(0.4850)						(0.1557)
CH4F α	-0.0023	-0.0005	0.0010	0.0011	-0.0008	0.0015	-0.0049	-0.0013	-0.0003	0.0027	-0.0003	0.0045
P-value						(0.4489)						(0.1254)

Panel C: Quintile Portfolios Constructed When Using $VVIX_{40,60}$												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0037	0.0055	0.0068	0.0080	0.0071	0.0034*	0.0020	0.0042	0.0061	0.0070	0.0084	0.0064*
P-value						(0.0894)						(0.0725)
CAPM α	-0.0040	-0.0013	0.0002	0.0012	-0.0008	0.0033	-0.0050	-0.0014	0.0007	0.0013	0.0013	0.0063*
P-value						(0.1257)						(0.0971)
FF3F α	-0.0034	-0.0005	0.0007	0.0018	-0.0002	0.0032	-0.0050	-0.0012	0.0008	0.0011	0.0013	0.0064*
P-value						(0.1385)						(0.0892)
CH4F α	-0.0034	-0.0005	0.0008	0.0019	-0.0002	0.0032	-0.0050	-0.0012	0.0007	0.0011	0.0014	0.0065*
P-value						(0.1221)						(0.0602)
Panel D: Quintile Portfolios Constructed When Using $VVIX_{60,80}$												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0036	0.0062	0.0070	0.0076	0.0067	0.0032*	0.0022	0.0045	0.0065	0.0068	0.0067	0.0046
P-value						(0.0864)						(0.1733)
CAPM α	-0.0043	-0.0006	0.0005	0.0008	-0.0011	0.0032	-0.0047	-0.0013	0.0011	0.0012	-0.0003	0.0044
P-value						(0.1116)						(0.2463)
FF3F α	-0.0033	0.0002	0.0009	0.0011	-0.0006	0.0028	-0.0048	-0.0009	0.0012	0.0007	-0.0004	0.0044
P-value						(0.1753)						(0.2770)
CH4F α	-0.0032	0.0002	0.0009	0.0012	-0.0005	0.0028	-0.0048	-0.0009	0.0012	0.0007	-0.0003	0.0045
P-value						(0.1896)						(0.2475)
Panel E: Quintile Portfolios Constructed When Using $VVIX_{80,max}$												
	Equal-Weighted						Value-Weighted					
	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Mean	0.0031	0.0062	0.0067	0.0085	0.0065	0.0034**	0.0038	0.0054	0.0054	0.0068	0.0050	0.0013
P-value						(0.0287)						(0.6084)
CAPM α	-0.0047	-0.0006	0.0001	0.0017	-0.0012	0.0035**	-0.0027	-0.0004	-0.0002	0.0013	-0.0019	0.0007
P-value						(0.0338)						(0.7822)
FF3F α	-0.0038	0.0000	0.0006	0.0021	-0.0005	0.0033*	-0.0025	-0.0006	-0.0002	0.0009	-0.0018	0.0007
P-value						(0.0516)						(0.7868)
CH4F α	-0.0038	0.0000	0.0006	0.0021	-0.0005	0.0033**	-0.0025	-0.0006	-0.0003	0.0009	-0.0017	0.0008
P-value						(0.0465)						(0.7788)

Table 5: Results for Portfolios Constructed on Significant VOV Betas

Notes: This table presents results from portfolios constructed using stocks with statistically significant β_i^{VOV} obtained using the CBOE VVIX index, the replicated $VVIX_{min,max}$, or each of corridor VVIX measures ($VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$). Portfolio P is constructed by using stocks with significantly positive β_i^{VOV}, whereas portfolio N is constructed by using stocks with significantly negative β_i^{VOV}. Portfolio "P-N" is constructed by holding a long position in portfolio P and a short position in portfolio N. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Portfolios Constructed When Using CBOE VVIX

	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0054	0.0093	0.0039*	0.0040	0.0055	0.0016
P-value			(0.0902)			(0.6225)
CAPM α	-0.0015	0.0019	0.0034	-0.0017	-0.0007	0.0010
P-value			(0.1766)			(0.7417)
FF3F α	-0.0007	0.0021	0.0028	-0.0017	-0.0011	0.0005
P-value			(0.2135)			(0.8641)
CH4F α	-0.0007	0.0022	0.0028	-0.0017	-0.0011	0.0006
P-value			(0.2143)			(0.8319)

Panel B: Portfolios Constructed When Using $VVIX_{min,max}$

	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0038	0.0095	0.0057**	0.0028	0.0090	0.0062*
P-value			(0.0297)			(0.0844)
CAPM α	-0.0032	0.0025	0.0057**	-0.0034	0.0030	0.0064
P-value			(0.0374)			(0.1062)
FF3F α	-0.0024	0.0028	0.0051**	-0.0033	0.0030	0.0063
P-value			(0.0678)			(0.1266)
CH4F α	-0.0023	0.0028	0.0051**	-0.0033	0.0031	0.0064
P-value			(0.0684)			(0.1102)

Panel C: Portfolios Constructed When Using $VVIX_{min,20}$

	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0046	0.0098	0.0052	0.0023	0.0106	0.0083**
P-value			(0.1134)			(0.0254)
CAPM α	-0.0028	0.0031	0.0060*	-0.0043	0.0046	0.0088**
P-value			(0.0622)			(0.0158)
FF3F α	-0.0024	0.0035	0.0058*	-0.0045	0.0045	0.0090**
P-value			(0.0554)			(0.0117)
CH4F α	-0.0023	0.0035	0.0058*	-0.0045	0.0045	0.0090**
P-value			(0.0565)			(0.0103)

Panel D: Portfolios Constructed When Using $VVIX_{20,40}$						
	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0043	0.0088	0.0045	0.0033	0.0097	0.0063*
P-value			(0.1490)			(0.0942)
CAPM α	-0.0025	0.0014	0.0039	-0.0024	0.0036	0.0060
P-value			(0.2354)			(0.1195)
FF3F α	-0.0017	0.0013	0.0029	-0.0018	0.0033	0.0051
P-value			(0.3487)			(0.1866)
CH4F α	-0.0017	0.0013	0.0030	-0.0018	0.0034	0.0052
P-value			(0.3043)			(0.1379)
Panel E: Portfolios Constructed When Using $VVIX_{40,60}$						
	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0043	0.0091	0.0048*	0.0030	0.0108	0.0078*
P-value			(0.0720)			(0.0553)
CAPM α	-0.0026	0.0020	0.0046	-0.0033	0.0047	0.0081*
P-value			(0.1008)			(0.0599)
FF3F α	-0.0023	0.0023	0.0045*	-0.0040	0.0047	0.0087*
P-value			(0.0871)			(0.0542)
CH4F α	-0.0023	0.0023	0.0046*	-0.0040	0.0048	0.0088**
P-value			(0.0730)			(0.0418)
Panel F: Portfolios Constructed When Using $VVIX_{60,80}$						
	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0057	0.0086	0.0029	0.0033	0.0088	0.0055*
P-value			(0.1681)			(0.0727)
CAPM α	-0.0014	0.0013	0.0027	-0.0027	0.0028	0.0055*
P-value			(0.2314)			(0.0963)
FF3F α	-0.0003	0.0017	0.0020	-0.0031	0.0025	0.0056
P-value			(0.3777)			(0.1164)
CH4F α	-0.0003	0.0017	0.0020	-0.0031	0.0026	0.0056
P-value			(0.3919)			(0.1073)
Panel G: Portfolios Constructed When Using $VVIX_{80,max}$						
	Equal-Weighted			Value-Weighted		
	N	P	P-N	N	P	P-N
Mean	0.0041	0.0081	0.0040*	0.0032	0.0092	0.0060**
P-value			(0.0504)			(0.0349)
CAPM α	-0.0028	0.0011	0.0039*	-0.0025	0.0030	0.0055*
P-value			(0.0604)			(0.0636)
FF3F α	-0.0021	0.0015	0.0036*	-0.0024	0.0031	0.0056*
P-value			(0.0755)			(0.0575)
CH4F α	-0.0021	0.0016	0.0036*	-0.0024	0.0032	0.0056*
P-value			(0.0762)			(0.0507)

Table 6: Portfolio Level Analyses during Turbulent Period

Notes: This table presents results from quintile portfolios constructed based on β_i^{VOV} obtained using the CBOE VVIX index, the replicated $VVIX_{min,max}$, or each of corridor VVIX measures ($VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$) during the period from January 2007 to December 2013. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolios Constructed on β_i^{VOV}							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0022	0.0027	0.0035	0.0057	0.0046	0.0025	(0.2591)
$VVIX_{min,max}$	0.0013	0.0026	0.0033	0.0055	0.0060	0.0047**	(0.0425)
$VVIX_{min,20}$	0.0003	0.0027	0.0045	0.0048	0.0065	0.0061*	(0.0743)
$VVIX_{20,40}$	0.0019	0.0025	0.0045	0.0045	0.0053	0.0033	(0.2904)
$VVIX_{40,60}$	0.0011	0.0020	0.0043	0.0060	0.0054	0.0043	(0.1116)
$VVIX_{60,80}$	0.0008	0.0037	0.0044	0.0051	0.0047	0.0039	(0.1453)
$VVIX_{80,max}$	0.0001	0.0038	0.0038	0.0058	0.0051	0.0050**	(0.0192)
Panel B: Value-Weighted Portfolios Constructed on β_i^{VOV}							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0001	0.0023	0.0021	0.0048	0.0024	0.0023	(0.5655)
$VVIX_{min,max}$	-0.0007	0.0005	0.0011	0.0041	0.0068	0.0075*	(0.0759)
$VVIX_{min,20}$	-0.0029	0.0009	0.0016	0.0033	0.0070	0.0099***	(0.0099)
$VVIX_{20,40}$	-0.0016	0.0004	0.0014	0.0059	0.0042	0.0058	(0.1878)
$VVIX_{40,60}$	-0.0014	0.0003	0.0023	0.0046	0.0067	0.0080	(0.1026)
$VVIX_{60,80}$	-0.0021	0.0011	0.0034	0.0039	0.0042	0.0063	(0.1851)
$VVIX_{80,max}$	0.0006	0.0017	0.0014	0.0041	0.0027	0.0022	(0.5512)

Table 7: Results for Double-Sorting Portfolios

Notes: This table presents results from portfolios constructed using double sorting. First, all stocks are divided into five groups based on the controlled characteristic. Then, within each group, stocks are further divided into five groups based on β_i^{VOV} obtained using the CBOE VVIX index, the replicated $VVIX_{min,max}$, or each of corridor VVIX measures ($VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$). Thus, we construct 25 value-weighted portfolios in each case. After this, we average five portfolios with similar level of β_i^{VOV} across five controlled-characteristic quintiles. Finally, we get five portfolios constructed on β_i^{VOV} with another characteristic controlled. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Double Sorting Portfolios Controlling for β_i^{MKT}							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0047	0.0068	0.0064	0.0067	0.0069	0.0022	(0.3500)
$VVIX_{min,max}$	0.0036	0.0056	0.0061	0.0065	0.0078	0.0041	(0.1030)
$VVIX_{min,20}$	0.0023	0.0052	0.0064	0.0065	0.0089	0.0066**	(0.0345)
$VVIX_{20,40}$	0.0036	0.0054	0.0062	0.0066	0.0077	0.0042	(0.1162)
$VVIX_{40,60}$	0.0038	0.0059	0.0062	0.0071	0.0072	0.0034	(0.2134)
$VVIX_{60,80}$	0.0041	0.0054	0.0067	0.0068	0.0064	0.0023	(0.4770)
$VVIX_{80,max}$	0.0044	0.0056	0.0065	0.0064	0.0052	0.0008	(0.7455)
Panel B: Double Sorting Portfolios Controlling for β_i^{VIX}							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0040	0.0057	0.0065	0.0065	0.0056	0.0016	(0.4862)
$VVIX_{min,max}$	0.0038	0.0044	0.0056	0.0065	0.0071	0.0034	(0.1966)
$VVIX_{min,20}$	0.0034	0.0045	0.0051	0.0068	0.0075	0.0041*	(0.0632)
$VVIX_{20,40}$	0.0022	0.0038	0.0060	0.0078	0.0059	0.0037	(0.1960)
$VVIX_{40,60}$	0.0032	0.0049	0.0063	0.0070	0.0072	0.0040	(0.1624)
$VVIX_{60,80}$	0.0029	0.0069	0.0050	0.0065	0.0065	0.0037	(0.2183)
$VVIX_{80,max}$	0.0050	0.0043	0.0055	0.0062	0.0052	0.0003	(0.8895)
Panel C: Double Sorting Portfolios Controlling for $Size$							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0039	0.0068	0.0057	0.0078	0.0063	0.0024	(0.1325)
$VVIX_{min,max}$	0.0035	0.0056	0.0063	0.0083	0.0066	0.0030*	(0.0730)
$VVIX_{min,20}$	0.0030	0.0060	0.0066	0.0066	0.0080	0.0049**	(0.0371)
$VVIX_{20,40}$	0.0040	0.0054	0.0070	0.0071	0.0070	0.0030	(0.1806)
$VVIX_{40,60}$	0.0033	0.0056	0.0069	0.0076	0.0071	0.0038**	(0.0450)
$VVIX_{60,80}$	0.0035	0.0059	0.0070	0.0073	0.0065	0.0029	(0.1118)
$VVIX_{80,max}$	0.0039	0.0057	0.0070	0.0075	0.0062	0.0023	(0.1210)

Panel D: Double Sorting Portfolios Controlling for B/M							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0030	0.0055	0.0051	0.0072	0.0060	0.0030	(0.1539)
$VVIX_{min,max}$	0.0020	0.0048	0.0053	0.0059	0.0085	0.0065**	(0.0149)
$VVIX_{min,20}$	0.0019	0.0044	0.0056	0.0066	0.0081	0.0062**	(0.0127)
$VVIX_{20,40}$	0.0020	0.0036	0.0055	0.0077	0.0068	0.0047*	(0.0676)
$VVIX_{40,60}$	0.0020	0.0043	0.0057	0.0065	0.0072	0.0052	(0.1008)
$VVIX_{60,80}$	0.0021	0.0047	0.0066	0.0057	0.0069	0.0048	(0.1483)
$VVIX_{80,max}$	0.0041	0.0046	0.0050	0.0071	0.0053	0.0012	(0.5939)
Panel E: Double Sorting Portfolios Controlling for Previous Return $r_{t-12,t-2}$							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0037	0.0056	0.0051	0.0060	0.0071	0.0034	(0.1179)
$VVIX_{min,max}$	0.0025	0.0048	0.0046	0.0069	0.0071	0.0046*	(0.0587)
$VVIX_{min,20}$	0.0023	0.0047	0.0054	0.0069	0.0073	0.0050**	(0.0130)
$VVIX_{20,40}$	0.0039	0.0039	0.0048	0.0068	0.0066	0.0027	(0.2526)
$VVIX_{40,60}$	0.0023	0.0056	0.0057	0.0057	0.0075	0.0053*	(0.0942)
$VVIX_{60,80}$	0.0023	0.0043	0.0062	0.0067	0.0070	0.0047	(0.1246)
$VVIX_{80,max}$	0.0045	0.0043	0.0049	0.0070	0.0046	0.0001	(0.9440)
Panel F: Double Sorting Portfolios Controlling for Previous Return r_{t-1}							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0035	0.0055	0.0059	0.0054	0.0082	0.0047**	(0.0290)
$VVIX_{min,max}$	0.0029	0.0038	0.0048	0.0062	0.0092	0.0063***	(0.0096)
$VVIX_{min,20}$	0.0023	0.0042	0.0051	0.0067	0.0099	0.0076***	(0.0020)
$VVIX_{20,40}$	0.0023	0.0041	0.0057	0.0059	0.0087	0.0064**	(0.0349)
$VVIX_{40,60}$	0.0024	0.0040	0.0061	0.0066	0.0086	0.0062**	(0.0278)
$VVIX_{60,80}$	0.0027	0.0046	0.0063	0.0065	0.0079	0.0052*	(0.0648)
$VVIX_{80,max}$	0.0034	0.0056	0.0049	0.0057	0.0068	0.0034	(0.1115)
Panel G: Double Sorting Portfolios Controlling for *Illiquidity*							
VVIX	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0049	0.0069	0.0058	0.0075	0.0077	0.0028*	(0.0949)
$VVIX_{min,max}$	0.0041	0.0058	0.0070	0.0081	0.0076	0.0035*	(0.0661)
$VVIX_{min,20}$	0.0033	0.0061	0.0072	0.0077	0.0083	0.0050*	(0.0515)
$VVIX_{20,40}$	0.0053	0.0057	0.0071	0.0073	0.0077	0.0024	(0.2894)
$VVIX_{40,60}$	0.0045	0.0055	0.0066	0.0088	0.0075	0.0030	(0.1463)
$VVIX_{60,80}$	0.0044	0.0060	0.0074	0.0077	0.0073	0.0029	(0.1335)
$VVIX_{80,max}$	0.0045	0.0061	0.0073	0.0079	0.0070	0.0025	(0.1865)

Table 8: Predictive Horizon of VOV Betas

Notes: This table presents results from value-weighted portfolios constructed based on β_i^{VOV} obtained using the CBOE VVIX index, the replicated $VVIX_{min,max}$, or each of corridor VVIX measures ($VVIX_{min,20}$, $VVIX_{20,40}$, $VVIX_{40,60}$, $VVIX_{60,80}$, and $VVIX_{80,max}$). After the quintile portfolio construction, in order to investigate the predictive horizon of β_i^{VOV}, portfolios are assumed to be held by various horizons, e.g. 5 trading days, 10 trading days, 15 trading days, 1 calendar month, 2 calendar months, and 3 calendar months. P-values are calculated using Newey-West method and presented in parentheses. *, **, and *** denote for significance at 10%, 5% and 1% levels, respectively.

Panel A: Return on Value-Weighted Quintile Portfolios in Future 5 Trading Days							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	-0.0005	-0.0004	0.0000	0.0002	-0.0016	-0.0011	(0.5987)
$VVIX_{min,max}$	-0.0015	-0.0004	-0.0003	0.0002	-0.0005	0.0009	(0.4608)
$VVIX_{min,20}$	-0.0022	-0.0002	0.0006	0.0005	-0.0002	0.0020*	(0.0663)
$VVIX_{20,40}$	-0.0016	-0.0006	0.0005	0.0002	-0.0008	0.0008	(0.6166)
$VVIX_{40,60}$	-0.0020	-0.0005	0.0002	0.0000	0.0000	0.0021	(0.1779)
$VVIX_{60,80}$	-0.0016	-0.0003	0.0002	0.0000	-0.0009	0.0006	(0.6911)
$VVIX_{80,max}$	-0.0010	0.0000	-0.0006	0.0005	-0.0016	-0.0005	(0.7221)
Panel B: Return on Value-Weighted Quintile Portfolios in Future 10 Trading Days							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	-0.0007	0.0008	0.0019	0.0032	0.0016	0.0023	(0.3117)
$VVIX_{min,max}$	-0.0017	0.0008	0.0013	0.0031	0.0034	0.0051**	(0.0227)
$VVIX_{min,20}$	-0.0028	0.0011	0.0019	0.0029	0.0036	0.0064***	(0.0035)
$VVIX_{20,40}$	-0.0026	-0.0002	0.0021	0.0033	0.0030	0.0055**	(0.0109)
$VVIX_{40,60}$	-0.0022	0.0010	0.0020	0.0027	0.0035	0.0057**	(0.0263)
$VVIX_{60,80}$	-0.0020	0.0012	0.0019	0.0026	0.0028	0.0047*	(0.0657)
$VVIX_{80,max}$	-0.0002	0.0015	0.0014	0.0031	0.0001	0.0003	(0.8445)
Panel C: Return on Value-Weighted Quintile Portfolios in Future 15 Trading Days							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	-0.0005	0.0031	0.0037	0.0047	0.0021	0.0027	(0.3494)
$VVIX_{min,max}$	-0.0005	0.0024	0.0032	0.0043	0.0047	0.0053*	(0.0610)
$VVIX_{min,20}$	-0.0016	0.0027	0.0031	0.0038	0.0054	0.0071***	(0.0076)
$VVIX_{20,40}$	-0.0006	0.0015	0.0031	0.0051	0.0040	0.0047*	(0.0855)
$VVIX_{40,60}$	-0.0009	0.0022	0.0035	0.0046	0.0051	0.0060*	(0.0789)
$VVIX_{60,80}$	-0.0005	0.0027	0.0034	0.0044	0.0034	0.0039	(0.2310)
$VVIX_{80,max}$	0.0001	0.0031	0.0029	0.0050	0.0017	0.0016	(0.4517)

Panel D: Return on Value-Weighted Quintile Portfolios in Future 1 Months							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0029	0.0050	0.0058	0.0078	0.0058	0.0028	(0.3078)
$VVIX_{min,max}$	0.0022	0.0045	0.0050	0.0069	0.0085	0.0063**	(0.0301)
$VVIX_{min,20}$	0.0004	0.0047	0.0055	0.0068	0.0090	0.0086***	(0.0041)
$VVIX_{20,40}$	0.0018	0.0038	0.0051	0.0085	0.0071	0.0053*	(0.0854)
$VVIX_{40,60}$	0.0020	0.0042	0.0061	0.0070	0.0084	0.0064*	(0.0725)
$VVIX_{60,80}$	0.0022	0.0045	0.0065	0.0068	0.0067	0.0046	(0.1733)
$VVIX_{80,max}$	0.0038	0.0054	0.0054	0.0068	0.0051	0.0013	(0.6084)
Panel E: Return on Value-Weighted Quintile Portfolios in Future 2 Months							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0088	0.0114	0.0130	0.0143	0.0123	0.0035	(0.4816)
$VVIX_{min,max}$	0.0083	0.0113	0.0112	0.0131	0.0150	0.0068	(0.1445)
$VVIX_{min,20}$	0.0065	0.0123	0.0122	0.0131	0.0127	0.0063	(0.1038)
$VVIX_{20,40}$	0.0078	0.0108	0.0118	0.0155	0.0118	0.0039	(0.4848)
$VVIX_{40,60}$	0.0077	0.0105	0.0135	0.0129	0.0151	0.0074	(0.1940)
$VVIX_{60,80}$	0.0068	0.0105	0.0123	0.0141	0.0149	0.0081	(0.1097)
$VVIX_{80,max}$	0.0106	0.0119	0.0125	0.0124	0.0122	0.0017	(0.6690)
Panel F: Return on Value-Weighted Quintile Portfolios in Future 3 Months							
	1	2	3	4	5	5-1	P-value
CBOE $VVIX$	0.0141	0.0178	0.0190	0.0217	0.0212	0.0071	(0.2106)
$VVIX_{min,max}$	0.0147	0.0169	0.0178	0.0201	0.0234	0.0087	(0.1006)
$VVIX_{min,20}$	0.0133	0.0195	0.0186	0.0194	0.0203	0.0070	(0.1697)
$VVIX_{20,40}$	0.0138	0.0168	0.0190	0.0228	0.0183	0.0045	(0.4432)
$VVIX_{40,60}$	0.0143	0.0159	0.0207	0.0193	0.0222	0.0079	(0.2045)
$VVIX_{60,80}$	0.0125	0.0159	0.0189	0.0205	0.0238	0.0113**	(0.0349)
$VVIX_{80,max}$	0.0167	0.0177	0.0196	0.0185	0.0204	0.0037	(0.4281)